ESTIMATION OF THERMAL PARAMETERS OF BUILDINGS THROUGH INVERSE MODELING AND CLUSTERING FOR A PORTFOLIO OF BUILDINGS

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ABSTRACT

Estimating heat transfer parameters of building envelope for existing buildings is challenging due to limited data from sensors and meters. In this study, we have developed a method for estimating heat transfer parameters of building envelope through clustering technique with inverse modeling for portfolio of buildings. Firstly, we derived a static heat transfer model from a system of dynamic equations by integrating the equations for different time periods. The model links monthly energy usage with cooling and heating loads, and latent heat loads. Secondly, temporal data from a building was used to estimate the overall heat transfer parameters. Thirdly, a clustering scheme was developed to segment all buildings in the portfolio into different clusters based on similarity criteria. The overall heat transfer parameters are then separated into different heat transfer coefficients for wall, roof and window using data from multiple buildings in the same cluster. We describe an application of this method to K-12 school buildings in the New York City.

INTRODUCTION

Building energy consumption is a major source for energy consumption and greenhouse gas emission. In the United States, 40% of the nations total energy consumption occurs in commercial and residential buildings (DOE (2006)). Also the buildings contribute to 45% of the country's greenhouse gas (GHG) emissions, which are linked directly to global climate change (EPA-ESPM (2009)). In order to control the growth of energy consumption and greenhouse gas emission, it is helpful to make buildings energy efficient by retrofitting, such as updating HVAC (Heat Ventilation and Air Conditioning) systems and improving insulation of walls, roofs and windows for the existing buildings and by updating the building code, enforcing building developer regulation and designing energy efficient buildings.

In order to reduce energy consumption in buildings, one needs to understand patterns of energy usage and heat transfer as well as characteristics of building structures, operations and occupant behaviors that influence energy consumption. There are two approaches for analyzing efficiency of the existing buildings based on measured data. One approach is to use statistical methods to put all potential influence factors into certain regression models and to conduct multiple statistical analyses. For instance, the gross square foot of the building, the number of occupants, age of buildings and operational hours of the building would be some natural candidates that affect total energy usage. The cooling degree days and heating degree days related to weather condition are also important factors that affect total energy usage (Kissock J.K. and D.E. (2003)).

The other approach is from physical perspective. Heat gain or loss of a building is through the building envelope due to conduction, convection, infiltration and solar radiation (Ashrae (2009)). Heat gain also comes from sensible loads, including heat from lightings, electric devices and occupancy body inside the building. HVAC systems including boilers, chillers and air handling units (AHU) are used to reduce temperature inside buildings during summer and to increase temperature during winter to achieve a comfortable climate inside the building for tenants. Physical properties of the building, like thermal resistance of wall, roof and window, infiltration through openings and solar heat gain through different parts of envelope, are important parameters that can be helpful for identifying energy savings opportunities. When designing and building a new building, these thermal parameters are typically available from engineering and architectural data, and a forward modeling method (such as DOE (2010)) is often used to analyze energy performance of the buildings in various conditions. In the forward modeling method, the dynamic equation of thermal energy balance is constructed and used to simulate the profiles of temperature and other systems variable inside the building. But for the existing buildings, the engineering and architectural data are not typically available, and building energy performance would have degraded over time; therefore, an inverse method can be the better way to estimate the thermal parameters of the buildings. The inversion method uses sensor data such as inside temperature, outside temperature, air flow rate, supply temperature of AHU and etc. to estimate the physical parameterś values through parameter estimation techniques.

For the modeling of buildings, we typically face a challenge in implementing the inversion method due to the lack of data required, since it is not always possible to design experiment to collect required data from buildings which are occupied. The observed data through unintrusive sensors might not allow us to estimate all parameters. For the portfolio of commercial buildings that are analyzed for this work, we only have monthly energy usage data. In this paper, we present an innovative procedure to address this issue. First, we derive a static heat transfer model through integration and seasonal separation. Second, multiple monthly data are used for estimating the overall heat transfer coefficient and solar contribution for each building. Lastly, a clustering schema is proposed to separate the overall insulation coefficient parameter into thermal resistance of wall, roof and window for a collection of similar buildings.

Overview of Physical Modeling Approach

In this section, we describe information flow and the overall modeling approach of this research. Our focus is to estimate buildingś thermal parameters from limited observation data. The parameters we aim at recovering include thermal resistance of wall and roof, thermal transmittance of window, air infiltration rate through building envelope. We base our model on the idea that the higher the resistance of the building envelope to the change of outside climate, such as high temperature and low temperature, the less energy is required to make the climate comfortable for occupants inside the building.

There are two approaches for estimating thermal parameters of a building. One is forward modeling approach, which requires detailed data on material used and engineering design. Then there are empirical formulas to estimate the corresponding thermal parameters (Ashrae (2009)). Architects and engineers typically use this approach to design new building and estimate energy performance. This forward modeling approach may not be feasible for existing buildings because the engineering data and design documents are often not available and building may have gone through changes and degradation that have not been documented. The other approach comes into place in this case, i.e. associating these parameters with observables and estimating these parameter values through inversion of physical model prescribed by a set of differential equations (partial or ordinary).

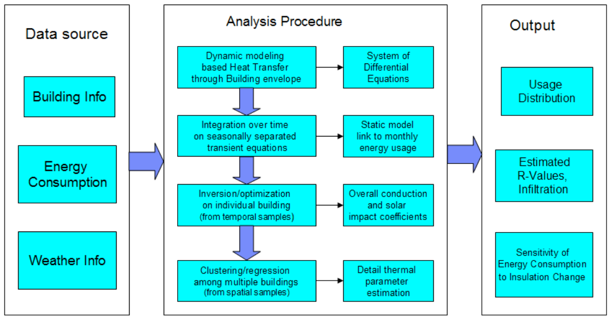

Figure 1: Physical Modeling Process

Figure 1 shows the inversion process consisting of data input, analytic procedure and output. Input data includes static building information and dynamic (time dependent) weather data and energy consumption data. Analytic procedure starts with a physical model that describes heat transfer through the building envelope. Such approach has been presented in several papers (Smith (1997), Vala (2002), Kerestecioglu A. and Gu (1989)). Although inversion model based on dynamical data was studied in some paper (Chahwane L. and Q. (2009), Chen and A.K. (2003) & Abushakra (1997)), it was unpractical in our study due to lack of detailed sensor data.

In this study, we propose a novel approach for building thermal parameters estimation. Firstly, a physics-based heat transfer model is derived from time integration and seasonal separation. Here, monthly thermal energy consumption is associated with the building thermal properties as well as overall weather change in that month. Secondly, by fitting the model with multiple monthly data, the overall insulation coefficient of the building can be obtained. However, it is impossible to decompose the overall insulation coefficient into thermal parameters related to walls, roofs and windows. Thirdly, we use clustering techniques to estimate thermal parameters related to walls, roofs and windows. We assume that there are multiple buildings with roughly same physical parameters but with different dimensions, which we can cluster into different groups based on similar characteristics. Finally, all thermal parameters are obtained from the regression model for each cluster.

The analytic procedure results in thermal parameters estimation. The physical model derived in the first step can be used to generate heating loss or gains through different parts of envelope and usage distribution between heating and cooling. Finally, sensitivity analysis can be carried out for how energy consumption changes as insulation condition changes.

Physical Model Derivation

We start with heat and moisture transfer equations through a building envelope. By integration of these equations over certain time-periods, the balance equations for cooling and heating seasons is derived to account for different thermal energy requirement. For the cooling season during summer time, it is required to use air-conditioner to cool down temperature and to dehumidify air inside a building. For the heating season during winter time, it is required to heat up temperature and possibly to humidify air inside a building. We derive a proper heat transfer model for the total energy usage in a certain period, associated to heating gain or loss via conduction, convection and radiation through the building envelope.

Schematic Description

Similar to Rabl (1988) and McKinley and A.G. (2008) and in analogy to electronic circuit notation, we can express heat transfer by a network of capacitors and resistors for heat conduction through a building envelope as shown in Figure 2. Thermal resistance (R-value) is used to measure the effectiveness of an insulator and defined as the ratio of temperature difference across an insulator and the heat flux (heat transfer per unit time per unit area). We use the notation of R_{wall}, R_{win} and R_{roof} for R-values of wall, window and roof respectively in Figure 2. Thermal heat capacity is used to measure the capability of storing heat inside the object and it is defined as the ratio of the amount of heat energy transferred into the object and the resulted increase in temperature of the object. Usually, we use specific heat capacity (C-value) heat capacity per unit of mass. We denote by C_{wall}, C_{roof} and C_{air} the specific heat of wall, roof and air inside the building in Figure 2. Thermal transmittance (U-value) is the reciprocal of R-value, and is commonly used for windows. Heat can also be infiltrated into the building when exchanging air through opened windows and doors as well as through other openings and cracks in the building envelope, intentionally or un-intentionally. The symbol M_{inf} in Figure 2 is for air exchanging rate corresponding to infiltration and natural ventilation. The symbol Q_{sys} represents the air flow from HVAC system, which is used to adjust temperature and humidity inside the building to provide the comfort for the occupants. Another main source that influences temperature of wall, roof and zone is coming directly from solar radiation on building envelope surfaces.

Dynamical Model Equations

We now derive the system of equations that correspond to the schematic graph in Figure 2. These equations are based on the first principal of thermodynamics and conservation law of energy and mass (i.e., moisture content).

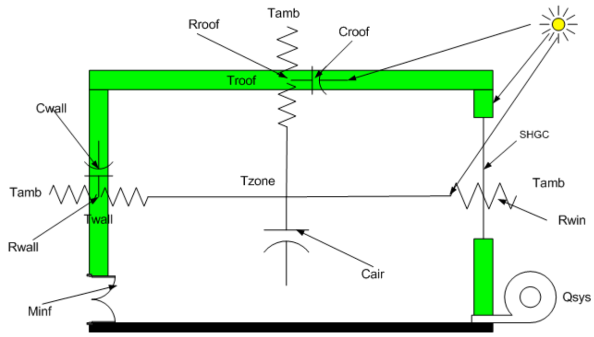

Figure 2: Network of Resistors and Capacitors

$$\rho_{air}C_{air}V_z\frac{dT_z}{dt} = \frac{2A_{wall}}{R_{wall}}\left(T_{wall}-T_z\right)+\frac{2A_{roof}}{R_{roof}}\left(T_{roof}-T_z\right)$$
$$+\frac{2A_{win}}{R_{win}}\left(T_{amb}-T_z\right)+\rho_{air}C_{air}m_{inf}A_{leak}\left(T_{amb}-Tz\right)$$
$$+Q_{sol}\lambda_{shgc}A_{win}+\Sigma Q_{hi}+\rho_{air}C_{air}m_{sys}\left(T_{sys}-T_z\right) \tag{1}$$

$$\rho_{wall}C_{wall}A_{wall}d_{wall}\frac{dT_{wall}}{dt} = \frac{2A_{wall}}{R_{wall}}\left(T_{amb}-T_{wall}\right)$$
$$+\frac{2A_{wall}}{R_{wall}}\left(T_z-T_{wall}\right)+Q_{sol}\lambda_{wall}A_{wall} \tag{2}$$

$$\rho_{roof}C_{roof}A_{roof}d_{roof}\frac{dT_{roof}}{dt} = \frac{2A_{roof}}{R_{roof}}\left(T_{amb}-T_{roof}\right)$$
$$+\frac{2A_{roof}}{R_{roof}}\left(T_z-T_{roof}\right)+Q_{sol}\lambda_{roof}A_{roof} \tag{3}$$

$$\rho_{air}C_{air}V_z\frac{dT_z}{dt} = \rho_{air}m_{inf}A_{leak}\left(W_{amb}-W_z\right)$$
$$+\Sigma Q_{wi}+\rho_{air}m_{sys}W_{sys}\rho_{air}m_{ret}W_z \tag{4}$$

Where

$\rho_{air},\rho_{wall},\rho_{roof}$: Density of air, wall and roof $\left(\frac{lb}{ft^3}\right)$

$C_{air},C_{wall},C_{roof}$: Air, wall & roof specific heat capacity $\left(\frac{Btu}{F\cdot lb}\right)$

$A_{wall},A_{roof},A_{win}$: Area od wall, roof and window $\left(ft^2\right)$

d_{wall},d_{roof}: Thickness of wall and roof (ft)

A_{leak}: Leakable area surrounding zone $\left(ft^2\right)$

$R_{wall},R_{roof},R_{win}$: R-value for wall, roof and window $\left(\frac{h\cdot F\cdot ft^2}{Btu}\right)$

T_{wall},T_{roof}: Temperature of wall and roof (F)

T_z,T_{amb},T_{sys}: Zone, ambient & system (AHU) temperature (F)

V_z: Volume inside zone $\left(ft^3\right)$

W_z: Zone moisture (moisture mass over dry air mass) $\left(\frac{lb_w}{lb_{da}}\right)$

W_{amb},W_{sys}: Moisture content of ambient & supply air $\left(\frac{lb_w}{lb_{da}}\right)$

m_{inf}: Infiltration rate $\left(\frac{ft^3}{h\cdot ft^2}\right)$

m_{sys}: Supply air flow rate of AHU system $\left(\frac{ft^3}{h}\right)$

m_{ret}: Return air flow rate of AHU system $\left(\frac{ft^3}{h}\right)$

Q_{sol}: Solar radiation per hour per unit area $\left(\frac{Btu}{h\cdot ft^2}\right)$

λ_{shgc}: Solar heat gain coefficient of glass (dimensionless)

$\lambda_{wall},\lambda_{roof}$: Wall & roof solar heat absorption coefficient

(dimensionless)
Q_{hi}: Sensible load from electronic devices & occupants $\left(\frac{Btu}{h}\right)$
Q_{wi}: Moisture load from furniture surfaces & occupants $\left(\frac{lb_w}{h}\right)$
h_υ: Specific enthalpy related to latent head $\left(\frac{Btu}{lb_w}\right)$
Q_{sys}, Q_{tsys}: Total & thermal system energy consumption rate $\left(\frac{Btu}{h}\right)$
Q_{csys}, Q_{hsys}: Cooling & heating system energy consumption rate $\left(\frac{Btu}{h}\right)$
$q_{eff}, q_{cef}, q_{hef}$: Energy usage efficiency of total, cooling and heating system

Equation 1 is for thermal energy balance for the air inside the building. The left hand side (LHS) of the equation is the accumulation of enthalpy for inside of building per unit time. The first term on the right hand side (RHS) is for heat convection from wall, the second term is for heat convection from roof and the third term is for heat convection from window. The fourth term is for air exchange between inside and outside of the building. The fifth term is contribution from solar radiation through window. The sixth term is for sensible heat loads emitted from equipment and occupants. The last term is the thermal energy adjustment from HVAC system.

The second and third equations describe the similar energy balance for wall and roof. LHS of these equations represent accumulation of enthalpy inside of wall and roof respectively. On RHS, there are three terms for thermal contribution. The first term is heat convection from outside air into the wall. The second term is heat convection from wall to inside the building (i.e., zone). The third term accounts for thermal energy from solar radiation. Note that we assume there is no heat capacity inside the window, and do not include a similar equation for window here. We consider this approximation valid since windowś heat capacity is small due to its thickness, in comparison to wall and roof. Equation (4) describes moisture balance which results from air exchange with outside and supply and return air from and to the Air Handling Unit (AHU).

Reduction through Season Separation and Time Integration

Energy is consumed in both heating and cooling seasons, and historic energy consumption data are typically available in monthly level. Therefore, it is necessary to separate the heat transfer equations for different seasons and to integrate the separated equations over monthly period so that the integration of the system term would correspond to monthly usage.

Multiplying by $\frac{1}{2}$ both sides of the equation (2) and regrouping the first and second terms in RHS of the equation (2), we have

$$\frac{1}{2}\rho_{wall}C_{wall}A_{wall}d_{wall}\frac{dT_{wall}}{dt} = \frac{A_{wall}}{R_{wall}}\left(T_{amb}-T_z\right) - \frac{2A_{wall}}{R_{wall}}\left(T_{wall}-T_z\right) + \frac{1}{2}Q_{sol}\lambda_{wall}A_{wall}. \quad (5)$$

Similarly, from the equation (3), we have

$$\frac{1}{2}\rho_{roof}C_{roof}A_{roof}d_{roof}\frac{dT_{roof}}{dt} = \frac{A_{roof}}{R_{roof}}\left(T_{amb}-T_z\right) - \frac{2A_{roof}}{R_{roof}}\left(T_{roof}-T_z\right) + \frac{1}{2}Q_{sol}\lambda_{roof}A_{roof}. \quad (6)$$

Adding the equations (5) and (6) to the equation (1) and then equation(4) multiplied by h_υ, we obtain

$$\begin{aligned}
&\rho_{air}C_{air}V_z\frac{dT_z}{dt} + \frac{1}{2}\rho_{wall}C_{wall}A_{wall}d_{wall}\frac{dT_{wall}}{dt} \\
&+\frac{1}{2}\rho_{roof}C_{roof}A_{roof}d_{roof}\frac{dT_{roof}}{dt} + h_\upsilon\rho_{air}V_z\frac{dW_z}{dt} \\
&= \frac{A_{wall}}{R_{wall}}\left(T_{amb}-T_z\right) + \frac{A_{roof}}{R_{roof}}\left(T_{amb}-T_z\right) \\
&+\frac{A_{win}}{R_{win}}\left(T_{amb}-T_z\right) + Q_{sol}\lambda_{shgc}A_{win} \\
&+\frac{1}{2}Q_{sol}\lambda_{wall}A_{wall} + \frac{1}{2}Q_{sol}\lambda_{roof}A_{roof} + \sum Q_{hi} \\
&+h_\upsilon\sum Q_{wi} + \rho_{air}C_{air}m_{\inf}A_{leak}\left(T_{amb}-T_z\right) \\
&+h_\upsilon\rho_{air}m_{\inf}A_{leak}\left(W_{amb}-W_z\right) \\
&+\rho_{air}C_{air}m_{sys}\left(T_{sys}-T_z\right) + h_\upsilon\rho_{air}\left(m_{sys}W_{sys}-m_{ret}W_z\right) \quad (7)
\end{aligned}$$

We assume that T_z, T_{wall} and T_{roof} are constant during one month period. Multiplying equation(7) by $sgn\left(T_{amb}-T_z\right) - sgn\left(T_z-T_{amb}\right)$ and then integrating it over one period, we obtain

$$\begin{aligned}
&\left(\frac{A_{wall}}{R_{wall}} + \frac{A_{roof}}{R_{roof}} + \frac{A_{win}}{R_{win}}\right)\int_{t_0}^{t_1}\left((T_{amb}-T_z)^+ + (T_z-T_{amb})^+\right)d\tau \\
&+\left(\lambda_{shgc}A_{win} + \frac{1}{2}\lambda_{wall}A_{wall} + \frac{1}{2}\lambda_{roof}A_{roof}\right)\cdot \\
&\int_{t_0}^{t_1}Q_{sol}\left(sgn\left(T_{amb}-T_z\right) - sgn\left(T_z-T_{amb}\right)\right)d\tau \\
&+\sum_i\int_{t_0}^{t_1}\left(Q_{hi}+h_\upsilon Q_{wi}\right)\left(sgn\left(T_{amb}-T_z\right) - sgn\left(T_z-T_{amb}\right)\right)d\tau \\
&+\rho_{air}A_{leak}\int_{t_0}^{t_1}m_{\inf}\left(C_{air}\left((T_{amb}-T_z)^+ + (T_z-T_{amb})^+\right)\right. \\
&\left.+h_\upsilon\left(W_{amb}-W_z\right)\left(sgn\left(T_{amb}-T_z\right) - sgn\left(T_z-T_{amb}\right)\right)\right)d\tau \\
&= \rho_{air}C_{air}\int_{t_0}^{t_1}m_{sys}\left(\left(T_z-T_{sys}\right)^+ + \left(T_{sys}-T_z\right)^+\right)d\tau \\
&+h_\upsilon\rho_{air}\int_{t_0}^{t_1}\left(m_{sys}W_{sys}-m_{ret}W_z\right)\left(sgn\left(T_{amb}-T_z\right)\right. \\
&\left.-sgn\left(T_z-T_{amb}\right)\right)d\tau \quad (8)
\end{aligned}$$

Assuming that $\left(T_z-T_{sys}\right)\left(T_{amb}-T_z\right) > 0$ and T_{sys} plays an opposite role compared with T_{amb} and actually adjusts temperature inside the zone. When choosing T_z to be equal to the set point temperature, the first term in (8) would be the sum of cooling degree hours (CDH) and heating degree hours (HDH) of the given month.

$$\int_{t_0}^{t_1}\left((T_{amb}-T_z)^+ + (T_z-T_{amb})^+\right)d\tau = \sum_j\left(CDH_j+HDH_j\right)\Delta\tau_j$$

$$\int_{t_0}^{t_1}Q_{sol}\left(sgn\left(T_{amb}-T_z\right) - sgn\left(T_z-T_{amb}\right)\right)d\tau = \sum_j Q_{sol}(j)\frac{CDH_j-HDH_j}{CDH_j+HDH_j}\Delta\tau_j$$

$$\int_{t_0}^{t_1} m_{\inf}(C_{air}\left((T_{amb}-T_z)^+ + (T_z-T_{amb})^+\right)$$
$$+h_\upsilon\left(W_{amb}-W_z\right)\left(sgn\left(T_{amb}-T_z\right)-sgn\left(T_z-T_{amb}\right)\right))d\tau =$$
$$m_{\inf}(C_{air}\sum_j\left(CDH_j+HDH_j\right)\Delta\tau_j+$$
$$h_\upsilon\sum_j\frac{DMH_j\cdot CDH_j+HMH_j\cdot HDH_j}{CDH_j+HDH_j}\Delta\tau_j)$$

where the term DMH is dehumidifying hour and HMH is humidifying hour. The index j is for time when hour is taken as the base unit. So $\Delta\tau_j = 1$ when data are available in hour. Finally, equation (8) can be rewritten as,

$$\begin{aligned}
&\left(\frac{A_{wall}}{R_{wall}}+\frac{A_{roof}}{R_{roof}}+\frac{A_{win}}{R_{win}}\right)\sum_j\left(CDH_j+HDH_j\right)\Delta\tau_j\\
&+\rho_{air}A_{leak}m_{\inf}(C_{air}\sum_j\left(CDH_j+HDH_j\right)\Delta\tau_j\\
&+h_\upsilon\sum_j\frac{DMH_j\cdot CDH_j+HMH_j\cdot HDH_j}{CDH_j+HDH_j}\Delta\tau_j)\\
&+\left(\lambda_{shgc}A_{win}+\frac{1}{2}\lambda_{wall}A_{wall}+\frac{1}{2}\lambda_{roof}A_{roof}\right)\cdot\\
&\sum_j Q_{sol}(j)\frac{CDH_j-HDH_j}{CDH_j+HDH_j}\Delta\tau_j\\
&+\sum_i\sum_j\left(Q_{hi}(j)+h_\upsilon\cdot Q_{wi}(j)\right)\frac{CDH_j-HDH_j}{CDH_j+HDH_j}\Delta\tau_j\\
&=\sum_j\frac{\lambda_{cef}Q_{csys}(j)\cdot CDH_j+\lambda_{hef}Q_{hsys}(j)\cdot HDH_j}{CDH_j+HDH_j}\Delta\tau_j\\
&=\lambda_{eff}\sum_j Q_{sys}(j)\Delta t_j
\end{aligned}\tag{9}$$

After grouping the terms with either CDH or HDH (in numerators), we get separated static models for cooling and heating usages. We only describe the static model for whole energy usage.

Static Heat Transfer Model

Data of some terms in Equation (9) might not be available, for instance, loading rate in the fourth term of LHS. In such case, we would take the gross floor area (GFA) and the number of people (NOP) who use the building as an approximation. Usually, we have the monthly energy usage from monthly usage bill. In order to complete the model, we need to include non-thermal energy usage, like hot water, cooking facilities (ventilation attaching to them) etc. A base usage, the non-thermal energy usage, is added to the left and total energy usage is substituted on the right. We conclude the following static heat transfer model

$$\begin{aligned}
&\lambda_{env}A_{env}\sum_j\left(p_cCDH_j+p_hHDH_j\right)\Delta\tau_j\\
&+\lambda_{\inf}\rho_{air}A_{leak}\sum_j(C_{air}\left(p_cCDH_j+p_hHDH_j\right)\\
&+h_\upsilon\frac{p_cCDH_j*DMH_j+p_h*HDH_j*HMH_j}{CDH_j+HDH_j})\Delta\tau_j\\
&+\lambda_{base}\sum_j\sqrt{GSF\cdot NOP_j}\Delta\tau_j\\
&+\lambda_{load}\sum_j\sqrt{GSF\cdot NOP_j}\frac{p_cCDH_j-p_hHDH_j}{CDH_j+HDH_j}\Delta\tau_j\\
&+\lambda_{sol}A_{env}\sum_j Q_{sol}(j)\frac{p_cCDH_j-p_hHDH_j}{CDH_j+HDH_j}\Delta\tau_j = q_{eff}\sum_j Q_{sys}(j)\Delta\tau_j
\end{aligned}\tag{10}$$

where p_c is the percentage area being air-conditioned and p_h the percentage area being heated,

$$\begin{aligned}
A_{env} &= A_{wall}+A_{roof}+A_{win}\\
\frac{A_{wall}}{R_{wall}}+\frac{A_{roof}}{R_{roof}}+\frac{A_{win}}{R_{win}} &= \lambda_{env}A_{env}\\
\lambda_{wall}A_{wall}+\lambda_{roof}A_{roof}+\lambda_{shgc}A_{win} &= \lambda_{sol}A_{env}
\end{aligned}\tag{11}$$

Five parameters $\lambda_{env}, \lambda_{inf}, \lambda_{base}, \lambda_{load}, \lambda_{sol}$ are needed to be determined. Comparing Eq.(10) with Eq (9), parameter λ_{env} is for the overall heat transfer; parameter λ_{inf} corresponds to infiltration m_{inf} through the openings of the building envelope; parameter λ_{base} is for the non-thermal energy consumption; λ_{load} is for sensible loads that have heating contribution; and λ_{sol} is for the overall solar contribution coefficient. In order to make them comparable across different buildings, the overall heat transfer and solar contribution are normalized by the area of building envelope; the non-thermal base load and the sensible load are normalized by the geometrical average of GFA and NOP. Note that a fundamental difference between overall heat transfer (first) and infiltration (second) is from inclusion of DMH and HMH in the infiltration, since moisture could not get into the building via heat transfer (e.g., heat conduction and convection). Also it should be noticed that the impact from both sensible load and solar contribution is different for cooling and heating seasons. During cooling season, additional energy is needed to offset the heat from sensible load and solar radiation, while during heating season, less energy is used due to contribution from sensible load and solar radiation.

Thermal Parameter Estimation

Overview of estimation procedure

Figure 3 shows the flow of estimating parameters. Top four boxes describe data used in the procedure. The first is for monthly energy usage, reported in monthly statement from energy providers. The second is a list of buildings with dimension information, from which we can calculate the area of wall, roof and window, the volume of the building, and might also include operation characteristics, like total occupancy, operation hours, and number of electrical appliances and equipment. The third is related to temperature, cooling degree hours and heating degree hours for each day within a month, which are calculated from the difference between outside air temperature and the set point temperature inside the building. Note that the set point could be different for cooling and heating and for daytime verse nighttime. Similarly, the forth is related to humidity, humidifying hours (HMH) during winter and dehumidifying hours (DMH) during summer compared with a comfortable humidity level. Under the assumption that moisture is not transferred by heat conduction and convection into the building and is only infiltrated into the building, the DMH and HMH may help us to separate overall heat conduction through building envelope with overall air exchange and infiltration. Based on all data described above, we can separate the total energy usage into cooling, heating and non-thermal energy usages. Further, the derived static model can be used for each individual building with multiple monthly usages to estimate total heat transfer coefficient and solar contribution coefficients. Finally, we apply clustering technique on the collection of buildings and separate the overall conduction coefficient into values for different thermal parameters

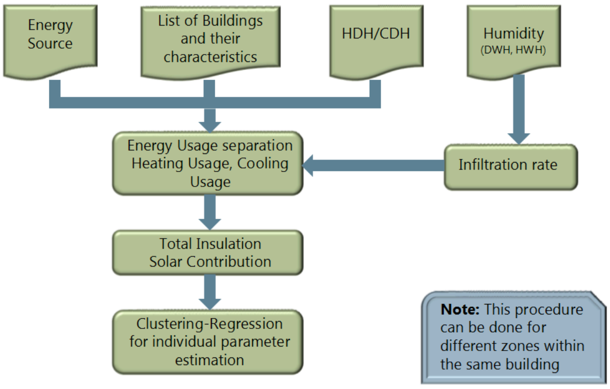

Figure 3: Parameter estimation flowchart

Inversion process from temporal observable data

Now we need to estimate the five parameters $\lambda_{env}, \lambda_{inf}, \lambda_{base}, \lambda_{load}, \lambda_{sol}$ in Eq. (10). For easy illustration of the inversion process, we introduce a matrix L with dimension $5 \times N_m$ where N_m is the number of months with available data and we use k to denote monthly index. For each month k, the entries of the matrix L are expressed as

$$L[1,k] = A_{env} \sum_j \left(p_c CDH_j + p_h HDH_j\right) \Delta\tau_j$$

$$L[2,k] = \rho_{air} A_{leak} \sum_j (C_{air} \left(p_c CDH_j + p_h HDH_j\right)$$

$$+ h_\upsilon \frac{p_c CDH_j * DMH_j + p_h * HDH_j * HMH_j}{CDH_j + HDH_j}) \Delta\tau_j$$

$$L[3,k] = \sum_j \sqrt{GSF \cdot NOP_j} \Delta\tau_j$$

$$L[4,k] = \sum_j \sqrt{GSF \cdot NOP_j} \frac{p_c CDH_j - p_h HDH_j}{CDH_j + HDH_j} \Delta\tau_j$$

$$L[5,k] = A_{env} \sum_j Q_{sol}(j) \frac{p_c CDH_j - p_h HDH_j}{CDH_j + HDH_j} \Delta\tau_j$$

$$G[k] = \sum_j Q_{sys}(j) \Delta\tau_j$$

$$(\lambda_1, \lambda_2, \lambda_3, \lambda_4 \lambda_5) \triangleq (\lambda_{env}, \lambda_{\inf}, \lambda_{base}, \lambda_{load}, \lambda_{sol})$$

Then equation (10) can be rewritten as

$$\sum_{i=1}^{5} L[i,k] \lambda[i] = q_{eff} G[k]. \quad (12)$$

The term $G[k]$ on the RHS is from total energy usage for a month. The vectors $CDH, HDH, DMH, HMH, Q_{sol}$ in the matrix L for month k with dimension

$$N_{kd} = 24 \cdot \left(\text{numbers of days in the } k^{th} \text{ month}\right)$$

are calculated from weather data for hourly temperature, from comparing relative humidity and solar radiation strength with cooling and heating set points, comfortable relative humidity. In the case of no data of operation hours and occupancy being available, we assume some function form for the NOP vector that takes working days or school days with hours from 8AM to 6PM into consideration. Suppose that building dimension data are available to calculate the area (A_{env}) of the building envelope and gross floor area (GFA) and the percentage area being air-conditioned and heated is specified. All values of entries in L are determined. Since the equation (10) is derived from physical consideration, we expect that all five factors included in $L[i, \cdot]$ are relevant and significant from statistical viewpoint.

It might be difficult to separate heat gain from conduction and infiltration due to two reasons. Firstly, humidity control inside the building is not clear or strict compared with temperature control based on set point through the thermostat. Secondly, infiltration through door and window opening is largely influenced by occupant behavior. We would like to combine the least squared of differences with some penalty term to ration percentage on conduction and infiltration, and to specify certain range constraint for total conduction parameter

$$\min(\sum_k \left(\sum_{i=1}^{5} \lambda_i L[i,k] - q_{eff} G[k]\right)^2$$

$$+ \eta_1 \sum_k (0.75 * \lambda_1 L[1,k] - 0.25 * \lambda_2 L[2,k])^2)$$

$$\text{s.t. (recall } \lambda_{env} \triangleq \lambda_1 \text{ by definition)}$$

$$\frac{1}{A_{end}} \left(\frac{A_{wall}}{\max(R_{wall})} + \frac{A_{roof}}{\max(R_{roof})} + \frac{A_{win}}{\max(R_{win})}\right)$$

$$< \lambda_{env} < \frac{1}{A_{end}} \left(\frac{A_{wall}}{\min(R_{wall})} + \frac{A_{roof}}{\min(R_{roof})} + \frac{A_{win}}{\min(R_{win})}\right)$$

where the minimum and maximum of R-value for each would come from the listed value in ASHRAE handbook. Based on our experience, we can fit well over 90% of 1400 buildings.

The overall efficiency parameter q_{eff} is taking into account equipment efficiency as well as the effect of simultaneous heating and cooling in the same zone. The value was chosen based on engineering handbook suggestion and based on our experiment with the studied buildings.

Clustering process from a collection of buildings

The values of $\lambda_{env}, \lambda_{sol}$ that we got in the last subsection are overall heat transfer coefficient and solar contribution coefficients. Eq (11) gives the relationship between the overall coefficient and the parameters distributed to walls, roofs and windows. Using just one building dimension info, it is not possible to determine these parameters values for wall, roof and window due to its under-determinacy. When we have a collection of buildings with various dimensions but having physical similarities, it is possible to estimate these parameters values. The physical similarities could be due to different reasons, for instance, buildings built before 1970 may all use single-pane glasses. Buildings with same functionality and purpose (like for schooling) may use the same building code and same materials for wall and roof during certain period.

Mathematically, we can convert the building dimension data into a geometric point in a topological space. The distance of two points in the space corresponds to the closeness of similarity of two buildings. The K-Means clustering algorithm (Aldenderfer and R.K. (1984)& Blashfield 1984) can be used to put all buildings into several groups based on such topological information. We use a clustering technique consisting of an initial K-Means clustering and subsequent iterating until meeting a converging criterion. Figure 3 shows such a clustering process. Let S be the collection of buildings with size M, and S_n^k $(n = 1,2,\ldots,N)$ be a set of buildings that belong to the cluster n in the k^{th} iteration, where N is specified number of clusters. Then we have the following

$$S = \bigcup_{n=1}^{N} S_n^k, \quad S_i^k \bigcap S_j^k = \emptyset \; \forall i \neq j,$$

$$\sum_{n=1}^{N} size\left(S_n^k\right) = \sum_{n=1}^{N} M_n^k = size\,(S) = M,$$

where M_n^k is the number of buildings that belong to the set S_n^k.

For each cluster S_n^k $(n = 1,2,\ldots,N)$, the thermal parameters $R_{wall}[n]$, $R_{roof}[n]$and $R_{win}[n]$ can be obtained through regression over all buildings that belong to the cluster. The misfit for a building m_n that belongs to the cluster n is represented as

$$misfit\,[m_n] = abs(\frac{A_{wall}[m_n]}{R_{wall}[n]A_{env}[m_n]} + \frac{A_{wall}[m_n]}{R_{wall}[n]A_{env}[m_n]} + \frac{A_{wall}[m_n]}{R_{wall}[n]A_{env}[m_n]} - \lambda_{env}[m_n]) \qquad (13)$$

The total misfit for all buildings would be

$$misfit_{total}^{k} = \sum_{m=1}^{M} misfit[m].$$

The reshuffling step is processed as the following. For each given building m, we check its error against all N models,

$$error\,[m,n] = abs(\frac{A_{wall}[m]}{R_{wall}[n]A_{env}[m]} + \frac{A_{wall}[m]}{R_{wall}[n]A_{env}[m]} + \frac{A_{wall}[m]}{R_{wall}[n]A_{env}[m]} - \lambda_{env}[m])$$

and move this building into the one that gives the least error. After reshuffling, we have a new set of clusters S_n^{k+1} $(n = 1,2,\ldots,N)$ and need to create a new model for each cluster and to calculate a new $misfit_{total}^{k+1}$. When the related change is small enough, we stop further iterations and use the last set of models for parameters. Otherwise, we would continue the reshuffling step and create a new set of models for new clusters and check total misfit again until convergence.

Figure 5 gives another graphical demonstration on the clustering procedure. Initial clustering creates multiple clusters, indicated by "Buildings in cluster 1", "Buildings in cluster k". Each cluster has its own model in the sense that the result regressing coefficients are unique for each cluster. Then iteration begins to re-evaluate the ownership of each building. Buildings are reshuffled among there clusters so that the quantified misfit is minimized. The iteration is stopped until the total misfit does not change too much.

Note that, it is possible to cluster a collection of buildings by using different clustering algorithms or based on different building characteristics for initial clustering. A building could belong to different group under different clustering technologies. An algorithm may be developed to balance all contributions from different techniques. For instance, a weighted averaging scheme could be taken to estimate these parameters when multiple clustering techniques are adopted in the process.

Case Studies

We applied the static model to estimate parameters for the portfolios of New York City's K-12 public school buildings and campus buildings of McMaster University. A web-based GUI tool called *i-BEE*^{TM} (Lee Y. M. and Bel (2011)) was developed to present output resulting from our physical model. We give several examples in this section.

The first example is to show the estimated R-value for wall and roof and U-value for window for a given building. The building we considered has a total of 301,295 GSF and site energy usage of 9,961,200 kBtu annually. Combining with dimension data of roof area 60,259 ft^2, wall area 40,536 $ft^2$and window area 10,134 ft^2 as shown in Figure 6, we obtain from the model that R-value for wall is roughly 5.46 $[ft^2 \cdot {}^oF \cdot hour/Btu]$, R-value for roof is 11.06 $[ft^2 \cdot {}^oF \cdot hour/Btu]$ and U-value for window is 1.2 $\left[Btu/\left(ft^2 \cdot {}^oF \cdot hour\right)\right]$, and the infiltration rate is 0.23 [cfm/sf]. Based on these values, heat gain or loss through roof, wall and window can be calculated as shown in pie-graph of Figure 6.

Figure 7 shows the comparison of calculated energy usage with the observed monthly energy consumption. Energy usage calculation is based on Equation (10) with estimated parameters using procedure described in the last section.

Figure 8 shows the R-values of wall and roof for 954 buildings. After clustering procedure, we obtain two groups of clusters. One group contains all buildings with lower R-values (CL2, CL3 and CL4), and the other consists of buildings with higher R-values (CL1, CL5 and CL6). In fact, these values are consistent with overall expectation from building management team.

The second example is simulation of building insulation changes on energy consumption. *i-BEE*^{TM} computes thermal coefficients of individual buildings in the portfolio, such as R values for walls and roof, U value of windows and their infiltration coefficient, $\dot{m}_{\text{inf}}$. When a building is picked for analysis from the analytic dashboard, as shown in Figure 7, all those thermal coefficients are displayed and thermal energy for each month for a whole year is computed and shown. Then, a user changes one or more of the coefficients. In the example in Figure 5, a user changes the R-value of the roof from 16.68 to 40 $[ft^2 \cdot {}^oF \cdot hour/Btu]$ by hypothetically increasing insulation of the roof of the building. The toolset computes the energy savings by month and for the whole year. The yearly thermal energy consumption decreases by 325,792 kBtu from 8,124,482 kBtu to 7,798,690 kBtu.

The third example of simulation is for changing the thermostat set point of the building during the heating season. As shown in Figure 8, for another building in the portfolio, the heating set point is changed from 65 ^{o}F to 62 ^{o}F. The corresponding impact is computed as a decrease of yearly energy consumption by 653,703 kBtu from 5,045,111 kBtu to 4,391,408 kBtu.

Conclusion and Discussion

Starting with a system of dynamic thermal equations that describe heat transfer through a building envelope, we derive a static model by integration of the equations over different time periods with thermal requirements. Coefficients of terms in the model are associated with physical properties of buildings including thermal resistance and heat capacity of wall, roof and window. Combining with building dimension and dynamic weather data, the monthly energy usage is used to estimate the overall heat transfer and solar contribution parameters. A clustering algorithm is applied on all buildings under study to segment them into certain groups with similarity. After that, regression analysis for each group would separate the overall heat transfer and solar parameters into R-values for wall, roof and window. Primary validation based on data has been done and the results are promising. The estimated R-values are compatible to those suggested by ASHRAE handbook.

Further investigation is underway to collect weather data at building's location with detail temperature, humidity and solar radiation as well as more accurate building dimension data. We would like to achieve independence of all considered factors and avoid co-linearity of some data sets. The inversion modeling is very useful method to estimate underlying physical parameters based on measured data. For analysis of existing buildings which are occupied, the complexity of the heat transfer model is limited by the availability of data. For more meaningful and efficient parameter reconstruction, one can perform optimal experimental design for sensor deployment and data collection protocol. Inversion modeling in building energy field is not widely used yet and requires more research. We are also using dynamic observable data inside a building to estimate values of building physical parameters. If more detailed data is available, efficiency coefficient can be estimated based on detailed sensored data of demand and supply side.

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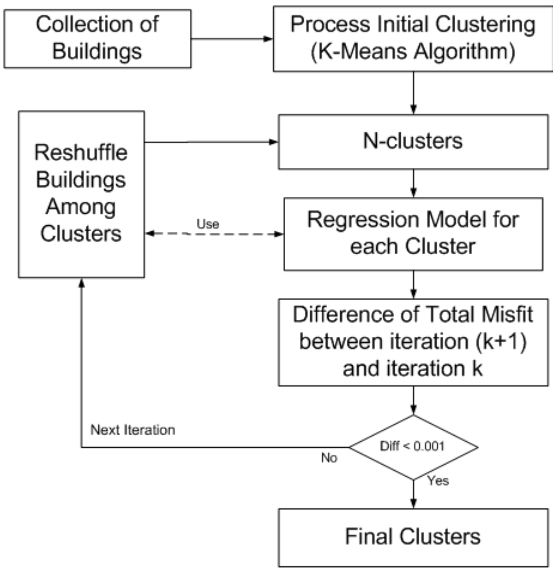


Figure 4: Clustering Process

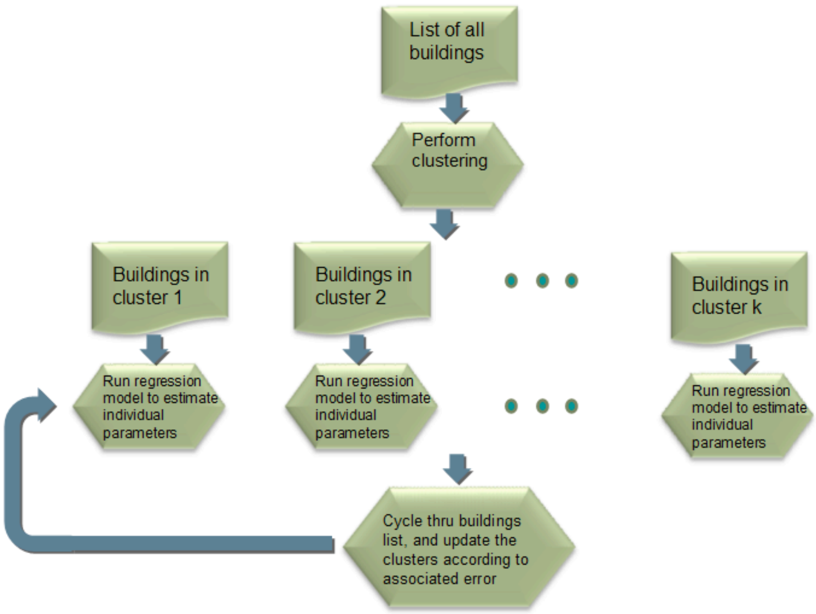
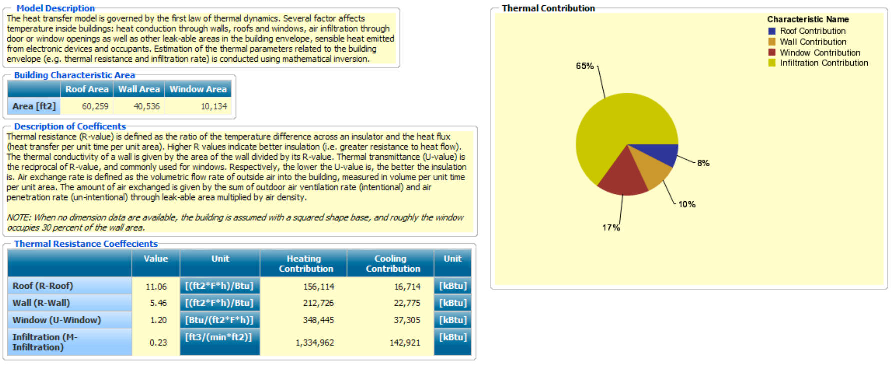


Figure 5: Clustering and Regression



Model Description

The heat transfer model is governed by the first law of thermal dynamics. Several factor affects temperature inside buildings: heat conduction through walls, roofs and windows, air infiltration through door or window openings as well as other leak-able areas in the building envelope, sensible heat emitted from electronic devices and occupants. Estimation of the thermal parameters related to the building envelope (e.g. thermal resistance and infiltration rate) is conducted using mathematical inversion.

Building Characteristic Area

	Roof Area	Wall Area	Window Area
Area [ft2]	60,259	40,536	10,134

Description of Coefficents

Thermal resistance (R-value) is defined as the ratio of the temperature difference across an insulator and the heat flux (heat transfer per unit time per unit area). Higher R values indicate better insulation (i.e. greater resistance to heat flow). The thermal conductivity of a wall is given by the area of the wall divided by its R-value. Thermal transmittance (U-value) is the reciprocal of R-value, and commonly used for windows. Respectively, the lower the U-value is, the better the insulation is. Air exchange rate is defined as the volumetric flow rate of outside air into the building, measured in volume per unit time per unit area. The amount of air exchanged is given by the sum of outdoor air ventilation rate (intentional) and air penetration rate (un-intentional) through leak-able area multiplied by air density.

NOTE: When no dimension data are available, the building is assumed with a squared shape base, and roughly the window occupies 30 percent of the wall area.

Thermal Resistance Coeffecients

	Value	Unit	Heating Contribution	Cooling Contribution	Unit
Roof (R-Roof)	11.06	[(ft2*F*h)/Btu]	156,114	16,714	[kBtu]
Wall (R-Wall)	5.46	[(ft2*F*h)/Btu]	212,726	22,775	[kBtu]
Window (U-Window)	1.20	[Btu/(ft2*F*h)]	348,445	37,305	[kBtu]
Infiltration (M-Infiltration)	0.23	[ft3/(min*ft2)]	1,334,962	142,921	[kBtu]

Figure 6: Thermal Parameters and Usage Distribution

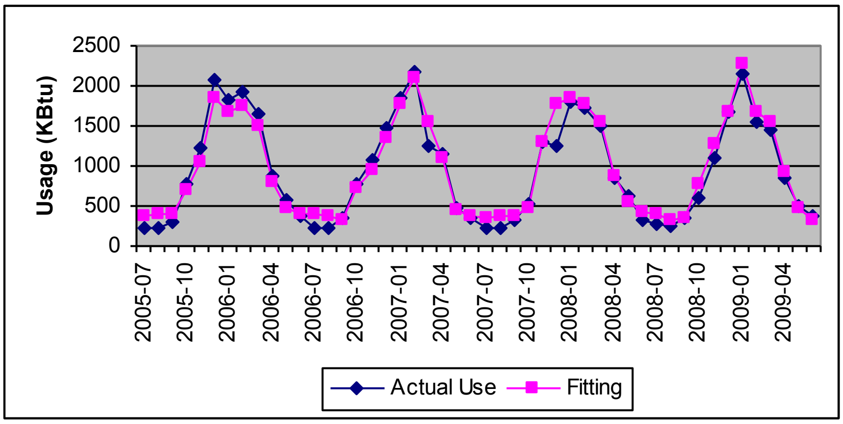


Figure 7: Actual Energy Usage vs. Simulated Usage

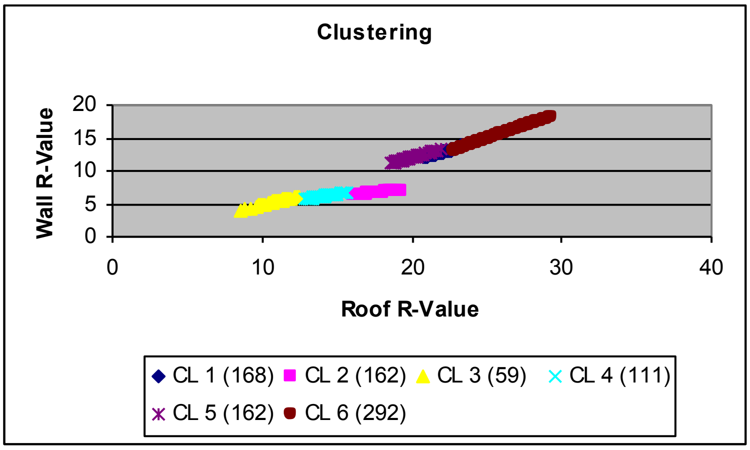


Figure 8: Clustering of 954 Buildings

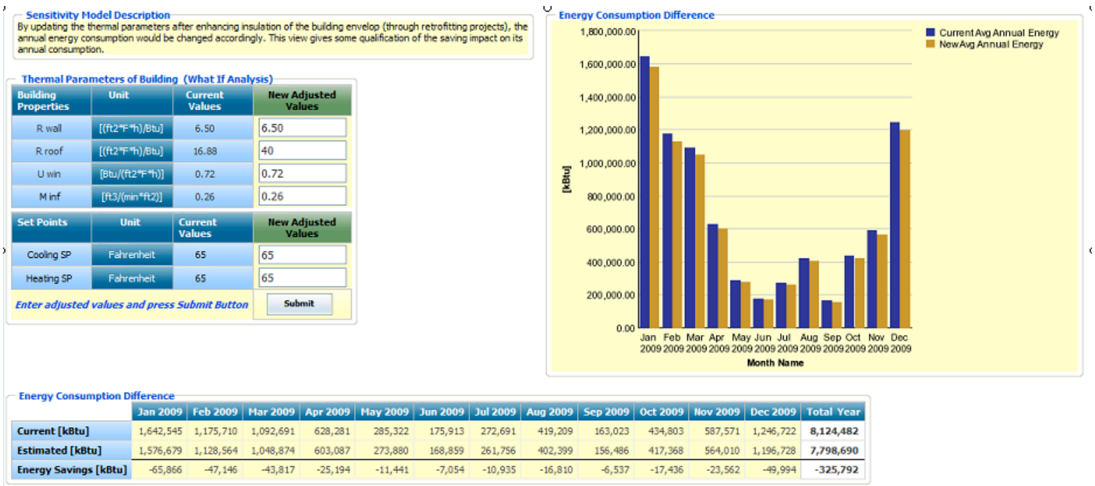


Figure 9: Simulation of Building Insulation Change

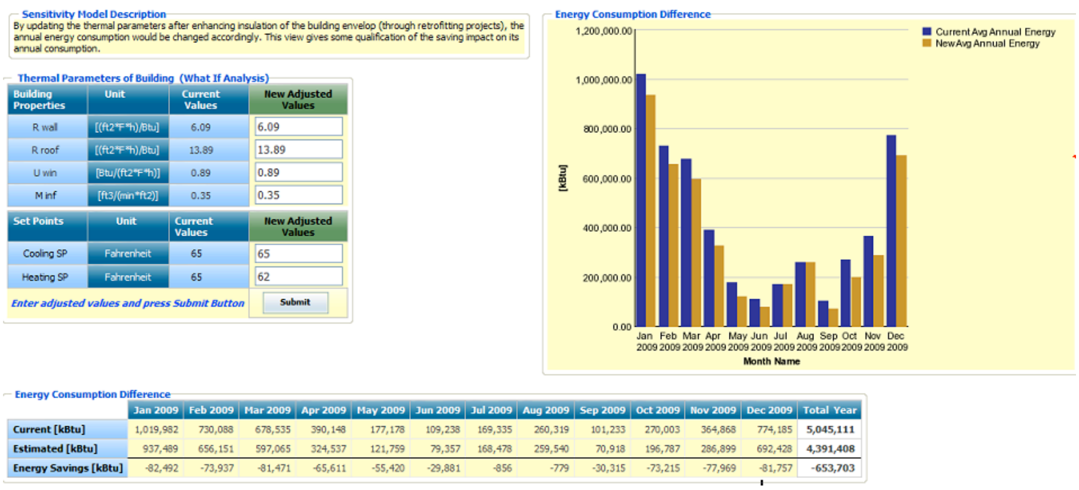


Figure 10: Simulation of the Point of Heating or Cooling